NASA Technical Memorandum 105998

IN-32
148079
p-22

Compressing Subbanded Image Data With Lempel-Ziv-Based Coders

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Prepared for the
Data Compression Conference
sponsored by the Institute of Electrical and Electronics Engineers
Snowbird, Utah, March 30 – April 1, 1993

NASA

(NASA-TM-105998) COMPRESSING SUBBANDED IMAGE DATA WITH LEMPEL-ZIV-BASED CODERS (NASA) 22 p

N93-20257

Unclas

G3/32 0148079

COMPRESSING SUBBANDED IMAGE DATA WITH LEMPEL-ZIV-BASED CODERS

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ABSTRACT

A method of improving the compression of image data using Lempel-Ziv-based coding is presented. Image data is first processed with a simple transform, such as the Walsh Hadamard Transform, to produce subbands. The subbanded data can be rounded to eight bits or it can be quantized for higher compression at the cost of some reduction in the quality of the reconstructed image. The data is then run-length coded to take advantage of the large runs of zeros produced by quantization. Compression results are presented and contrasted with a subband compression method using quantization followed by run-length coding and Huffman coding. The Lempel-Ziv-based coding in conjunction with run-length coding produces the best compression results at the same reconstruction quality (compared with the Huffman-based coding) on the image data used.

QUANTIZATION-BASED LOSSY COMPRESSION

A typical compression coding scheme for subbanded data uses run-length and Huffman coders on quantized data [1, 2, 3]. This is also the approach used in the

JPEG method for coding of the high frequency DCT coefficients. Statistical coders such as these should do well with data that has large peaks in their histograms at zero like those of the higher bands in subbanded data. The improvement in compressibility from this method comes from the quantization. Quantization maps (replaces) a range of values (in a "bin") onto one quantization value, reducing the variability of the data by restricting the number of possible values to a small number. The rounding of values to eight bits is actually quantization with small bin sizes.

By coarsely quantizing the data, some noise is removed along with some information, which improves the compression. With coarser quantization, the compression improves, but at a cost of added distortion to the reconstructed image. The key area for coarse quantization of subbands is the region around zero. Because of the peak of the histogram of a subband at zero, a deadband around zero will quantize more values to zero providing longer run-lengths at a cost of somewhat more distortion.

Quantization is the key difference between lossy and lossless coding. After quantization, compression is obtained by using lossless coders, such as run-length and Huffman coders. The loss all comes from the quantization stage.

This paper will present results from a subband compression approach to see if good lossy compression ratios can be obtained with LZ-based coding. The LZ-based coder is a public domain software program used on personal computers for general purpose text file compression and archiving (LHa by "Yoshi").

QUANTIZER SELECTION

Variations possible in quantizers include adaptive vs. fixed, midrise vs. midtread, symmetric vs. non-symmetric, uniform bin size vs. non-uniform, centered quantization values vs. centroid of pdf, bin size, deadband size, and threshold value. The type of quantizer that should be used can be deduced by looking at the histograms of subbands. These histograms have a peak around zero for all but the lowest band. Because of the basic similarities of the histograms of various images' subbands, adaptive quantizers will not be considered here.

To prepare the data for a run-length coder, we desire a lot of zero values. Because of the large number of subband values around zero, the type of quantizer that will provide a lot of zero values is a midtread quantizer (having a quantization bin with zero at the center). Because of the symmetry of the histograms, a symmetric quantizer around zero is also appropriate. The small probability of large values in the subband would suggest a non-uniform quantizer that provides larger bin sizes at higher values.

The quantization bin around zero is called a deadband. If a uniform quantizer was used with a large bin size (e.g., 32), then a deadband smaller than the uniform bin size may be necessary to minimize the difference between the reconstructed pixel value and the original pixel value. The size of a bin or deadband will affect the amount of distortion in the reconstructed image. The maximum error for a value in a particular bin is half the bin size for a quantizer with a centered quantization value. For a non-centered quantization value, the maximum possible error for any particular quantized value is larger, although the total error for all values may be lower. This raises the question: is it better to have fewer large errors or lots of smaller errors? Up to a certain bin size it is obviously better to have lots of smaller errors because those errors will not be noticeable. For example, a lot of errors of one count per pixel in an image will not be noticeable at all. Also, a large error in a high frequency region of the image should not be as serious as one in a low frequency area because of Human Visual System (HVS) masking, unless the high frequency is a lone edge where artifacts can be very noticeable.

A threshold is not appropriate for subbands because of the large errors that can be introduced. Even though a large value in a subband is very rare, the effect of clipping it off with a threshold can be noticeable. Large values occur at light/dark boundaries or edges, and the HVS is sensitive to noise near edges. Many images do not have any values in the subbands greater than a certain threshold, so the temptation is there to put one in since it will not degrade the test images at all. Bins at large values can be maintained at low cost because if they are not used their quantization values can be effectively removed with an entropy coder after the run-length coding.

There are four quantizer designs that will be used in this research: 1) a fine quantizer for the DPCM coding of the low band, 2) a fine quantizer for the subbands of high-quality reconstructions for scientific applications, 3) a coarse quantizer for the mid-bands of an entertainment-quality reconstruction, and 4) a very coarse quantizer for the highest band of the entertainment-quality reconstruction.

QUANTIZER DESIGN

Now that a midtread, non-uniform, symmetric quantizer has been selected, it remains to define the bins and the quantization values of each bin. To simplify the design somewhat, we can divide the design into three sections: 1) the deadband, 2) the low (near-zero) bins, and 3) the high (away from zero) bins. The quantizer will be applied to subbanded image data that has not been scaled or rounded to eight bit values, for example, 10 bit values for a four-band Walsh-Hadamard transform. If the subband values were rounded to eight bits before quantizing, additional distortions would be introduced. This is because rounding to eight bits is a uniform quantization, and a two-stage quantization will introduce additional distortion unless the bin boundaries for the second stage exactly match a subset of the bin boundaries for the first stage.

The deadband design is simply a matter of selecting the bin size since the quantization value will obviously be zero. A large bin size will result in longer runs of zeros and in increased distortion in the reconstructed image. A smaller bin size will result in fewer zero quantization values and in better reconstruction. The design trade is to make the bin as large as possible without introducing noticeable distortion due to quantization.

The low bins seem to fall naturally between ± 32 looking at the histograms of subbands. A bin size comparable to the deadband size may be appropriate. The quantization value for the low bins should be somewhat closer to zero than the center of the bin because of the curve of the histogram in the bin, at least for the bins nearest the deadband. The optimum place would be the centroid of the histogram in the bin, but that value will change from image to image. Since the histogram curve flattens out as it gets away from zero, it may not be worth the trouble to move the quantization value from the center for bins farther out.

Looking at the values beyond ± 32, large bins with centered quantization values are probably sufficient because there are not many values in any particular quantization bin, so the contribution to quantization noise by having a value at the center of the bin rather than at the centroid will be small.

For the DPCM quantizer, the number of bins is 31 with a deadband from -2 to +2 (see Table I). The fine quantizer has 63 bins with a deadband of -3 to +3. The two coarse quantizers have a deadband of -7 to +7, one with 7 and one with 15 bins. The quantizers generally have smaller bins near zero compared to bins away from zero since most subband values are expected to be near zero. The fine quantizer has a maximum bin size of nine with a quantization value at the center of the bin. Thus, no quantized value changes from its original value by more than four counts. The non-uniform quantizers used here are really made up of a couple of uniform quantizers with larger bin sizes used for the more extreme values. The subbanded data was processed such that the range of raw values was -255 to 255. This was accomplished by combining the transform scaling factor for analysis and synthesis into one scaling factor for analysis of 1/4.

RUN LENGTH CODER DESIGN

The run length coder for quantized subband values can be designed to take advantage of the structure of the data that we expect from the quantizer. The data should consist of many runs of zeros with some very long runs where there is little spatial high frequency information. The number of different non-zero values will be the same as the number of bins (less the deadband) in the quantizer, which should be considerably less than the number of possible values in the unquantized data. There will be runs of non-zero values also, but these will not be as long as the zero value runs.

To take advantage of this structure, the run length coder has been designed to encode the subbands into one or two byte long codewords representing runs of zeros or of up to sixteen different quantized values. This run length coder maintains bytesized codewords which simplifies handling of the data somewhat. The first bit of the codeword determines whether it represents a run of zeros or a run of non-zero values. Runs of zeros are coded with one or two bytes, while runs of non-zeros are coded with one byte only. The second bit in a codeword that represents a run of zeros indicates whether the length of the codeword is one or two bytes long. The remaining bits are the length of the run of zeros (up to 64 for a one byte codeword, and up to 16448 for a two byte codeword).

If the codeword represents a run of non-zero values, then four bits of the codeword represent the bin identification and the remaining three bits represent the length of the run (up to eight). The non-zero codewords can handle up to sixteen quantization bins with a run length of one to eight. The codewords use the following format:

<u>one byte zero codeword</u>

b7	b6	b5	b4	b3	b2	b1	b0
0	0	R	R	R	R	R	R

<u>two byte zero codewords</u>

b15	b14	b13	b12	b11	b10	b9	b8
0	1	R	R	R	R	R	R

b7	b6	b5	b4	b3	b2	b1	b0
R	R	R	R	R	R	R	R

non-zero, 16-bin codeword

b7	b6	b5	b4	b3	b2	b1	b0
1	B	B	B	B	R	R	R

where: B indicates bin identifying bits

R indicates run length bits

Because the high band quantization has 63 bins, the run length coder was modified for use with high band data to work with 64 bins. The change to increase the number of bins reduced the length of runs that can be coded to a maximum of two. The non-zero codewords for the 64 bin version follow the format below:

non-zero, 64-bin codeword

b7	b6	b5	b4	b3	b2	b1	b0
1	B	B	B	B	B	B	R

LOWEST BAND CODING

The classic approach of Gharavi and Tabatabai [1] uses a two-dimensional DPCM coder for the low band and a quantizer/run-length coder for the upper bands. The DPCM coder uses a third-order predictor using three previously decoded pixels, $x = 0.5A + 0.25B + 0.25C$, where x is the prediction, A is the previous horizontal pixel, B is the previous vertical pixel, and C is the previous diagonal pixel following B. In [1], the differential signal is quantized with 31 levels, symmetric, non-uniform quantization followed by a variable length coder.

The DPCM predictor from [1] will be used in this work, but with a different quantizer and entropy coder. The quantizer has a deadzone of ± 2 (following [2]), and bin sizes of 5 (low bins) and 23 (bins above 13) with no upper threshold. After quantization, an adaptive Huffman coder or LZ coder is used to provide compression. Table III gives the results for the four test images. The LZ-based coder results are better than the adaptive Huffman coder's for three of the four images. The image where the adaptive Huffman does better is the Baboon image where the result is about 10% better than for LZ. Run-length coding could be used before the statistical coders, but the added complexity was not justified by the small improvement in compression.

The low band coding determines the overall compression achieved because it is by far the hardest band to compress. The low band has nearly all of the signal energy of the original, and so is the biggest challenge to code. A high quality low band is required for good reconstruction.

The basic reconstruction quality possible with a given low band coding scheme can be estimated by using the low band alone to make a reconstruction. For a four band split, this can be done by doubling the horizontal and vertical lines of data to obtain a reconstructed image the same size as the original (basically by "zooming in"). The zoomed low band was used to give the base reconstructed PSNR values given in Table II.

If better compression ratios were desired in the following research, then improving the low band coding would be the place to start. A very good fidelity low band coder was used in this research because the interest here is in the coding of the higher subbands. The same low band coder was used in both the fine and coarse cases so that its effect on the results would be negligible. Better compression ratios can be achieved by trading more distortion in the reconstructed image. A larger deadband and coarser quantization of the DPCM data would be a place to start. Absolute compression ratios were not the goal of this research, rather a comparison of compression approaches was undertaken.

COMPRESSION RESULTS

The coding scheme described above was applied to subbanded image data from four test images. The Walsh-Hadamard transform was used to generate four bands for each image.

The resulting compression using the lossy technique is very good for entertainment quality images such as would be used for HDTV. Entertainment quality is the result of using the coarse quantizers. Table III contrasts the results for both fine and coarse quantizers resulting in high quality and entertainment quality reconstructions respectively. The compression ratio shown is for run-length followed by LZ-based coding.

The coarse quantization provided about a 50% improvement over the fine quantization in this case. The Baboon image proved hardest to compress because of its noise-like high frequency information. The noise-like nature of the image makes a lower quality reconstruction more tolerable, however. An easy improvement in compression without noticeable affect on quality can be obtained by dropping the high band completely, which results in a compression ratio of 3.4:1 for the fine quantizer and 5.3:1 for the coarse quantizer. The Baboon image is a nice one to use for testing compression because of the challenge of compressing the high frequency content, but not so good for finding distortion which is masked by the high frequencies.

LZ and adaptive Huffman coding are compared in Table IV. Adaptive Huffman coding was used to avoid the overhead incurred in transmitting the Huffman tree for every image. The comparison is between the higher bands of the test images in a four band split. In both cases the same quantizers and run-length coders are used, the difference is in the final coding stage. The LZ-based coder beats the Huffman coder in 19 out of 24 cases, sometimes by a factor of over 100. In the five cases where the Huffman coder outperformed LZ, the improvement was only around 10%. This occurred in images with lots of high frequency content (i.e., Baboon) which does not fit well with the model used by LZ coding. The surprising result is that the LZ-based coder works very well as a statistical coder for image data and that quantized, subbanded image data is generally well compressed using LZ. LZ-based coding also generally provided some improvement in compression for data that had already been Huffman coded.

CONCLUSION

The use of a Lempel-Ziv-based coder as a statistical coder for subbanded image data is very promising. Simple subbanding schemes can be used to prepare image data for compression by a text coder. This allows the use of commonly available archiving programs for compression of documents that include text and image data.

ACKNOWLEDGEMENTS

This work is based on research that was done in partial fulfillment of the requirements of the Doctor of Philosophy degree at the University of Toledo.

TABLE I

QUANTIZERS

DPCM 31 bins		FINE 63 bins		COARSE 1 (MID BANDS) 15 bins		COARSE 2 (HIGH BANDS) 7 bins	
BIN RANGE	VALUE	BIN RANGE	VALUE	BIN RANGE	VALUE	BIN RANGE	VALUE
-2-2	0	-3-3	0	-7-7	0	-7-7	0
3-7	5	4-7	5	8-31	20	8-63	20
8-12	10	8-12	10	32-61	41	64-190	127
13-25	17	13-17	15	62-102	82	191-255	254
26-42	34	18-22	20	103-143	123		
43-59	51	23-27	25	144-184	164		
60-76	68	28-31	30	185-225	205		
77-93	85	32-40	36	226-255	246		
94-110	102	41-49	45				
111-127	119	50-58	54				
128-144	136	59-67	63				
145-161	153	68-76	72				
162-178	170	77-85	81				
179-195	187	86-94	90				
196-220	212	95-103	99				
221-255	255	104-112	108				
		113-121	117				
		122-130	126				
		131-139	135				
		140-148	144				
		149-157	153				
		158-166	162				
		167-175	171				
		176-184	180				
		185-193	189				
		194-202	198				
		203-211	207				
		212-220	216				
		221-229	225				
		230-238	234				
		239-247	243				
		248-255	252				

Note: Quantizers are symmetric around zero. Only positive values are shown.

TABLE II

LOW BAND DPCM COMPRESSION RESULTS

IMAGE	FILE SIZE (bytes)			PSNR (dB)	BASE PSNR (dB)
	Quantized Original	Adaptive Huffman	LZ-Based		
LENNA Low Band	65,540	27,723	15,290	43.60	31.20
BABOON Low Band	65,540	27,327	30,489	38.85	23.23
IO Low Band	51,204	11,850	10,527	44.09	35.09
JUPITER Low Band	100,804	44,510	22,377	38.96	31.91
Original LENNA 512 x 512	262,148	73,254	83,379	43.51	43.51

Notes:

1. PSNR is calculated relative to the original low band data.
2. Base PSNR is calculated relative to the full size original image using only the low band quantized data for the reconstruction.

TABLE III

LOSSY COMPRESSION RESULTS
RUN LENGTH AND LZ-BASED CODING OF QUANTIZED, SUBBANDED DATA WITH DPCM CODED LOW BAND

LENNA	FINE QUANTIZATION	COARSE QUANTIZATION
PSNR (dB)	37.98	33.78
Compression Ratio (C.R.)	6.9 : 1	11.1 : 1

BABOON	FINE	COARSE
PSNR	35.68	28.77
C.R.	2.7 : 1	4.3 : 1

IO	FINE	COARSE
PSNR	40.33	36.34
C.R.	10.1 : 1	15.0 : 1

JUPITER	FINE	COARSE
PSNR	36.27	32.73
C.R.	6.9 : 1	12.5 : 1

TABLE IV

LZ-BASED VS. ADAPTIVE HUFFMAN COMPRESSION
OF QUANTIZED SUBBANDS

Image Data Identification	Original	Run-Length	Huffman	Huffman+ Run Len.	LZ	LZ + Run Len.	LZ+Huff.+ Run Len.
LENNA							
Fine Quantization							
HH	65,540	6,290	9,126	4,296	4,105	3,836	3,542
HL	65,540	18,150	13,026	11,044	12,073	11,153	10,468
LH	65,540	12,062	11,041	7,812	8,328	7,579	7,119
Coarse Quantization							
HH	65,540	1,721	8,368	1,690	1,202	1,122	1,127
HL	65,540	8,399	9,230	5,052	4,624	4,474	4,877
LH	65,540	4,354	8,764	3,459	3,002	2,781	3,210
BABOON							
Fine Quantization							
HH	65,540	35,837	17,345	18,016	19,788	18,920	17,910
HL	65,540	43,038	20,719	22,022	24,381	23,505	21,929
LH	65,540	44,162	25,053	25,211	27,475	25,176	25,176
Coarse Quantization							
HH	65,540	20,108	10,748	8,911	8,963	8,816	8,707
HL	65,540	24,201	11,362	10,374	10,544	10,438	10,208
LH	65,540	22,808	12,565	11,393	11,473	11,388	11,218

TABLE IV (cont)

LZ-BASED VS. ADAPTIVE HUFFMAN COMPRESSION
OF QUANTIZED SUBBANDS

Image Data Identification	Original	Run-Length	Huffman	Huffman + R.L.	LZ	LZ + R.L.	LZ + Huff + R.L.
IO							
Fine Quantization							
HH	51,204	1,056	6,528	1,271	802	757	1,059
HL	51,204	9,213	8,423	5,583	5,926	5,382	5,459
LH	51,204	5,843	7,671	4,088	4,114	3,681	3,938
Coarse Quantization							
HH	51,204	95	6,428	214	136	95	189
HL	51,204	3,296	6,780	2,585	2,105	1,986	2,382
LH	51,204	1,379	6,606	1,651	1,167	1,038	1,418
JUPITER							
Fine Quantization							
HH	100,804	8,644	13,645	5,821	5,661	5,318	5,585
HL	100,804	25,471	20,170	14,406	15,476	14,372	14,190
LH	100,804	29,198	17,270	16,925	17,788	16,406	16,846
Coarse Quantization							
HH	100,804	1,089	12,709	1,379	868	794	1,146
HL	100,804	5,991	14,021	4,634	4,183	3,938	4,388
LH	100,804	7,546	13,308	5,912	5,723	5,293	5,697

REFERENCES

1. Gharavi, H.; and Tabatabai, A.: Sub-Band Coding of Monochrome and Color Images. IEEE Trans. Circ. Sys., vol. 35, no. 2, Feb. 1988, pp. 207-214.

2. Jayant, N.S.; and Noll, P.: Digital Coding of Waveforms. Prentice-Hall, Englewood Cliffs, NJ, 1984.

3. Al-Asmari, A.Kh.; and Kwatra, S.C.: Bandwidth Compression of HDTV Images for Communication Via Satellite. AIAA Paper 92-2032, 1992.

4. Glover, D.: Subband/Transform Image Coding for Lossy and Lossless Compression. Ph.D. Thesis, The University of Toledo, Toledo, OH, 1992.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*

2. REPORT DATE
February 1993

3. REPORT TYPE AND DATES COVERED
Technical Memorandum

4. TITLE AND SUBTITLE
Compressing Subbanded Image Data With Lempel-Ziv-Based Coders

5. FUNDING NUMBERS
WU-144-10-10

6. AUTHOR(S)
Daniel Glover and S.C. Kwatra

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
National Aeronautics and Space Administration
Lewis Research Center
Cleveland, Ohio 44135-3191

8. PERFORMING ORGANIZATION REPORT NUMBER
E-7600

9. SPONSORING/MONITORING AGENCY NAMES(S) AND ADDRESS(ES)
National Aeronautics and Space Administration
Washington, D.C. 20546-0001

10. SPONSORING/MONITORING AGENCY REPORT NUMBER
NASA TM-105998

11. SUPPLEMENTARY NOTES
Prepared for the Data Compression Conference sponsored by the Institute of Electrical and Electronic Engineers, Snowbird, Utah, March 30-April 1, 1993. Daniel Glover, NASA Lewis Research Center, Cleveland, Ohio. S.C. Swatra, The University of Toledo, Toledo, Ohio 43606. Responsible person, Daniel Glover, (216) 433-2847.

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Unclassified - Unlimited
Subject Category 32

12b. DISTRIBUTION CODE

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A method of improving the compression of image data using Lempel-Ziv-based coding is presented. Image data is first processed with a simple transform, such as the Walsh Hadamard Transform, to produce subbands. The subbanded data can be rounded to eight bits or it can be quantized for higher compression at the cost of some reduction in the quality of the reconstructed image. The data is then run-length coded to take advantage of the large runs of zeros produced by quantization. Compression results are presented and contrasted with a subband compression method using quantization followed by run-length coding and Huffman coding. The Lempel-Ziv-based coding in conjunction with run-length coding procedures the best compression results at the same reconstruction quality (compared with the Huffman-based coding) on the image data used.

14. SUBJECT TERMS
Communications theory; Data compression; Coding

15. NUMBER OF PAGES
22

16. PRICE CODE
A03

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	